Improving ecosystem-based stock assessment and forecasting by using a hierarchical approach to link fish productivity to environmental drivers

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Background

A central feature of ecosystem-based fishery management is a broader consideration of environmental influences on stock productivity when assessing populations and setting harvest policies. Insights into environment-stock productivity relationships may be used in short term, tactical advice (e.g. annual catch limits) or in medium to long-term strategic advice that evaluates the long-term effectiveness of proposed harvest strategies in the face of climate change (A'mar et al. 2009). Thus, improved insight into how environmental factors affect stock productivity offers the promise of improved stock assessment and forecasting, especially when it allows for pre-emptive reductions in fishing effort on species likely to be worst affected. The emerging push for including ecosystem-based considerations in fisheries management decisions has therefore resulted in increased demands for information on how ecosystem dynamics affect fished stocks. *This proposal seeks to conduct a synthetic analysis of environmental drivers of fisheries productivity to improve our capability of incorporating these drivers into stock assessments and forecasts.*

Research regarding the direct inclusion of environmental information into stock assessments is still developing (Maunder and Watters 2003; Deriso et al. 2008; Schirripa 2009). Moreover, information on environmental links to stock productivity can be used to guide the specification of assessment models. For example, understanding environmentally forced changes in growth over time can be used to specify periods of good and poor growth in assessments. Hollowed et al. (2009) and A'mar et al (2009) demonstrate how long-term climate impacts on fish and fisheries can be predicted from a mechanistic understanding of how fish productivity responds to climate-sensitive environmental variables.

Given the large number of stocks that are presently managed by North Pacific and Pacific Fisheries Management Councils, the challenge of identifying key causative agents underlying production dynamics for each is daunting. This challenge is made even more difficult by the notorious problems that arise when attempting to identify causal relationships from serially autocorrelated time series data (Walters and Collie 1988; Myers 1998). Here we hypothesize that the process of including environmental information in stock assessments and forecasts can be improved by identifying groups of stocks that respond to environmental conditions in the same way. If this hypothesis is true, then the challenge is greatly simplified because instead of linking production to dynamic environmental features for each stock individually, one can predict the average response of groups of stocks that are expected to respond similarly. Therefore, our proposed work seeks to make a significant step forward for stock assessment and forecasting by using advances in numerical statistical methods that permit the estimation of hierarchical ensemble models.

There is considerable support for the notion that groups of stocks may respond to similar sets of environmental conditions. Previous studies revealed that patterns of recruitment variability in marine fishes showed similarities across species (Caddy and Gulland 1983) and these similarities produced recognizable patterns in population variability (Spencer and Collie 1997). In the North Pacific region, the well-known shift in the Pacific Decadal Oscillation transformed the ecosystems of Alaska and Northern California Current by enhancing the productivity of some species and diminishing the productivity of others (Anderson and Piatt 1999; Mantua et al. 1997; Hollowed et al. 2001). Mueter et al. (2007) demonstrated that in the Gulf of Alaska and eastern Bering Sea – Aleutian Islands, gadid and pleuronectid recruitment patterns were inversely related to each other, suggesting that stocks in these groups were responding to a common set of environmental forcing in opposing ways.

We propose to conduct a Bayesian hierarchical ensemble analysis to evaluate environmental drivers that govern the production dynamics of groundfish stocks in the Aleutian Islands, Gulf of Alaska and Northern California Current. These areas represent distinct ecosystems, and allow contrasts between groups of species that may be influenced by different environmental conditions. The statistical approach is ideally suited to identifying group-level effects of environmental features on populations: these models directly estimate the average effects of environmental drivers for entire groups of stocks (e.g. the average effect of SSH on recruitment for each group of stocks). These estimation models use information on all stocks simultaneously, resulting in enhanced statistical power and diminished probability of spurious correlations. By proposing a suite of candidate grouping / classification schemes and evaluating model fit for each alternative, we can identify which grouping scheme is best supported by the data. An additional strength of the Bayesian approach is that the resulting output (posterior probability distributions) can be used as an informative prior for data-poor stocks.

Approach

We view this project as a set activities consisting of (1) identifying ecologically relevant forcing functions and developing databases that contain time series for each; (2) collecting recruitment and growth data from target and non-target (likely growth only) fisheries data as time series and developing a database structure to house these data; (3) identifying candidate grouping structures for species i.e., what attributes of species might predispose them to respond to environmental forcing in similar ways? ; and (4) running Bayesian hierarchical models under alternative grouping structures to estimate the effects of environmental variables on productivity and to test which group structure is best supported by the data. We describe each of these activities in turn.

(1) Identifying causal linkages between environmental variables and dynamics of fish production is made difficult by the fact that many time series are autocorrelated. Environmental predictors of fish production often do not hold up over time as additional data are collected and spurious correlations can be a byproduct of testing multiple possible variables without having biologically-based and plausible *a priori* hypotheses (Myers 1998). For that reason we intend to populate a list of candidate environmental forcing functions that are based on mechanistic hypotheses.

We intend to build on the existing extensive body of research on the Gulf of Alaska and Northern

California current ecosystems (Hollowed et al. 2001; Holt and Punt 2009; Holt and Mantua 2009). This body of work has already identified linkages between local- and regional-scale environmental conditions and fish productivity on individual species or groups of species. Some of these include geographically-indexed SST and SSH data, ENSO and PDO indices, and upwelling indices. Ongoing research is using 3-D physical oceanographic models to predict sea temperatures-at-depth and current strengths, which may be more relevant for mid-water and bottom-dwelling species, particularly if species have a short pelagic larval duration and the critical period for survival depends on ecological processes occurring at depth.

(2) Recruitment and growth are two primary dimensions that describe the dynamics of fish productivity. Indeed, the fundamental theories of fish population dynamics point to survivorship during critical, often early life history periods as the primary determinant of variation in production (Cushing 1996). There are several lines of evidence to suggest that somatic growth can also play an important role. For instance, Pacific halibut (Clark et al. 1998) growth rates declined substantially over the past decades, resulting in downwards reduction in target harvest rates. Similarly, English Sole growth rates have declined from mid 1900's to present (Stewart 2007).

Temporal patterns of groundfish recruitment (or recruitment deviations) will be collated from age-structured stock assessments conducted by AFSC and NWFSC stock assessment scientists. Many of these data have already been compiled as part of the RAM Legacy database which includes catch, spawning biomass, total biomass, and recruitment time series for more than 300 individual stocks worldwide (Worm et al. 2009, Branch et al. 2010). Growth data are not currently part of the RAM legacy database and will need to be compiled from databases currently maintained by the AFSC and the NWFSC. At least two types of growth data are relevant. We can use size-at-age for fish that have fully recruited to the fishery (so that trends in exploitation rate would not alter size-at-age substantially). Alternatively, we can use age and length data to generate annual growth coefficients for each year class and species. All compiled data will be synthesized and merged into a sharable database structure that will ultimately become part of the RAM Legacy database, providing broad benefits to researchers.

(3) The central hypothesis of this proposed work is that groups of ecologically or taxonomically related species respond to some environmental drivers in similar ways. Therefore, identifying characteristics that define species groups is a crucial task. We approach this problem by developing hypotheses about the attributes that might define these groups, and pose alternative grouping structures as alternative hypotheses (and identify corresponding hypotheses for which environmental drivers might be relevant for each group). For instance, a simple grouping is based on geography and taxonomy: flatfish species in each major study region will respond in similar ways. Alternatively, we can sub-divide those classifications based on patterns of variability in production (Spencer and Collie 1997). Recently, Carrie Holt and others (unpublished report) devised a hierarchical grouping system that classified species on the basis of location of juvenile life stages, location of spawning, geography, and spawning season. Other additions might include duration of pelagic larval period (for recruitment) or trophic position (for growth). We anticipate developing and testing up to 10 separate classification / grouping schemes for analysis.

(4) Bayesian hierarchical ensemble modeling provides a significant advantage in providing enhanced statistical power, ability to estimate group-level mean effects, and to identify covariates upon which these group-level effect sizes rely (Qain et al. 2010; Essington and Paulsen 2010; Gelman and Hill 2003;

Stow and Scavia 2009). Hierarchical ensemble estimation is best understood as a generalization of random effects models in maximum likelihood estimation; coefficients (effect sizes) are estimated for individual stocks, but in a hierarchical structure whereby coefficient values for individual stocks are assumed to be drawn from a distribution described by a group-level mean and variance. Thus, the information in the data from other members of the group enhances the estimation of individual stock coefficients, thereby "borrowing strength from the ensemble". This is particularly important when relating recruitment and growth dynamics to environmental time series: this activity is prone to producing spurious results and statistical power is low because of autocorrelation in the data. Equally important for the present application are the group-level mean coefficients: the posterior distributions of these parameters can be used as priors for new species that are not part of this analysis.

We will use standard autoregressive time series models (e.g. Holt and Punt 2009; Hollowed et al. 2001) to link environmental variables to growth and recruitment. For analysis of growth data it will be important to consider ecologically appropriate lagged-effects (e.g. size at age X in year t may depend on conditions in year t, t-1….t-X). Holt and Punt (2009) used a Kalman filter to account for both process and observation error but concluded that process error far exceeds observation error. We will therefore use a simplified model structure that has only process error, which will permit the development of complexity in the form of multi-level parameter structure.

Because this is a Bayesian analysis, prior probability distributions for each parameter, including group level mean and variances (so called, hyperparameters) need to be specified. The most common tactic is to choose a non-informative prior so that the posterior distribution reflects the information content in the data. At times, weakly informative priors are needed, for instance to restrict the range of effect sizes so that they are biologically plausible. We will use the guidelines and procedures suggested by Gelman and Hill (2007) for setting weakly informative priors (e.g., half-cauchy distributions on hypervariance priors). Standard MCMC diagnostic procedures will be conducted for each model run (autocorrelation analysis, posterior predictive checks, Gelman-Rubin statistic). We will identify the grouping structure that is best supported by the data using Deviance Information Criteria.

We will hold one or more working group meetings with regional experts that are engaged in stock assessment, oceanographic monitoring and modeling, and fisheries ecology. Prior to the meeting(s), our research team will propose ways to classify recruitment patterns and possible statistical relationships with geographically indexed environmental indicators. During the workshop, invited experts will review the results and discuss proposed groupings.

Draft timeline
Summer-Autumn 2011: Identify/recruit graduate student. Begin organizing working group meeting (s). Plan data structure. Hold meetings with local experts. Begin environmental data collection. Begin collating time series of growth (size-at-age) and recruitment.

Winter-Spring 2012: hold additional meetings as needed, proceed with data collection and database production. Begin developing group structures (alternative hypotheses) for multi-level modeling. Begin coding (simulation testing, convergence issues). Begin initial Bayesian analyses on available time series. Prepare initial results for summer 2012 workshop

Summer – August 2012: Present findings at 2012 workshop, revise estimation or data use based on feedback at meeting. Finalize database structure (QA/QC) and prepare metadata so that database can be distributed

Winter- Summer 2013 Run final analyses, Begin manuscript preparation (thesis defense). Present final results at FATE meeting, submit manuscript for publication, and submit final report

Benefits

The capacity to predict likely effects of environmental drivers on groups of related stocks will greatly enhance forecasting and delivery of medium-term strategic scientific advice. These analyses can be used to generate priors for growth or recruitment rates in Bayesian stock assessment (e.g. SS2) for species that are currently being assessed. By identifying groups of species that respond similarly, we can provide a more efficient approach to linking environmental drivers to dynamics of productivity. Ultimately, when folded into stock assessments, we might be able to better bridge the gap between activities that monitoring ecosystem indicators and providing tactical (e.g. TAC setting) management advice. Thus, the products from this proposal are directly germane to the goals of the FATE program. Because our research team includes those that are directly engaged in stock assessment, we can ensure that we effectively convey our findings to the broader community of stock assessment scientists in the region. The results of this study will be relevant for fishery managers as they move towards more formally incorporating the principles of ecosystem based fishery management into their decision making process. Finally, we view this work as a demonstration of a generalized concept and approach that can be applied to multiple regions in the U.S. and elsewhere to improve ecosystem-based scientific advice.

Deliverables

1. A final report detailing results, posterior probabilities for alternative models, grouping structures best supported by the data, and detailed consideration of how the specific results can be applied to stock assessment and forecasting in these ecosystems.
2. A database of time series of environmental, and ecological data and time series of growth and recruitment
3. Standardized code (based in R, but calling ADMB / BUGS or JAGS) that can support future development and expansion of the multi-level estimation framework.

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